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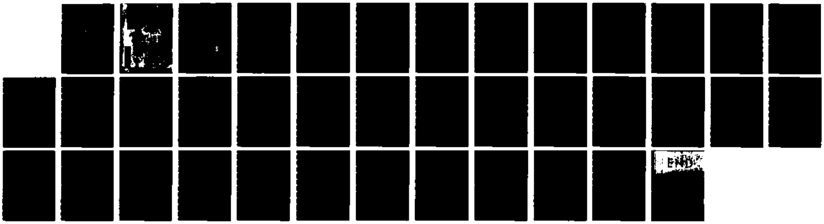

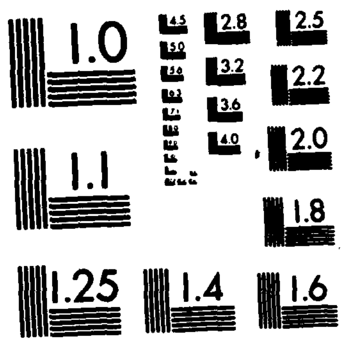

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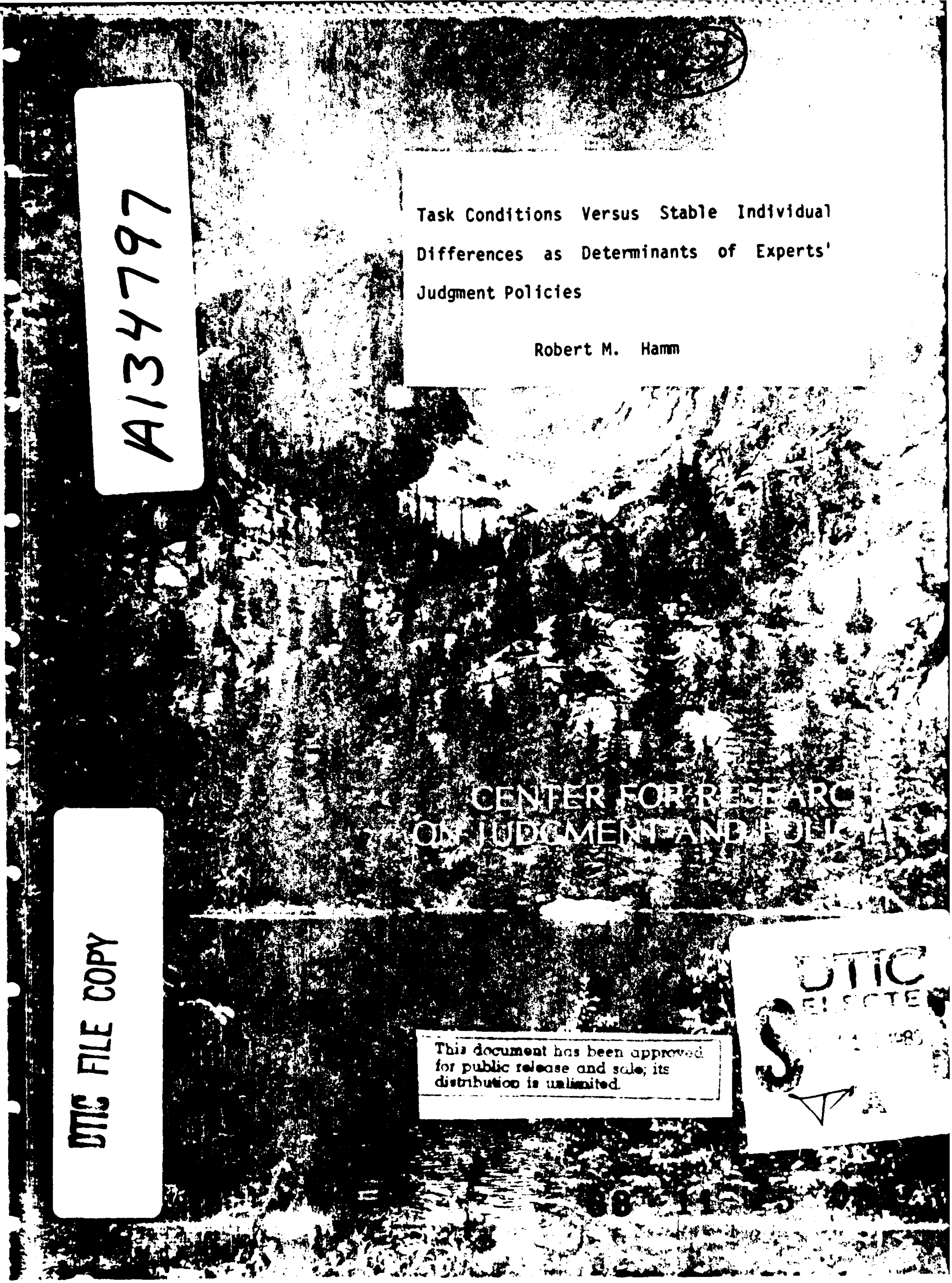
Task Conditions Versus Stable Individual Differences as Determinants of Experts' Judgment Policies

Robert M. Hamm



Task Conditions Versus Stable Individual Differences as Determinants of Experts' Judgment Policies

Robert M. Hamm

Institute of Cognitive Science

Center for Research on Judgment and Policy

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Report No. 249

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An analysis of twenty-one highway experts' judgments of the safety of a set of highways, under three different task conditions, was undertaken to determine whether task conditions or stable individual differences in judgment policy had the stronger role in determining the experts' judgment performances. Two analytical approaches were used: (a) comparing the correlations among performances within each individual expert over the different task conditions, and within each task over the different experts, and (b) clustering the

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20. ABSTRACT (Continued)

performances and inspecting whether clusters were made up primarily of performances from the same individuals or from the same task conditions. While the approach of comparing correlations of performances gave ambiguous results, the clustering approach clearly indicated that task condition, not stable individual judgment policy, determines similarities among judgment performances.

A-1

Introduction

Expert judgment in any field is thought to be a careful, reliable process based on a formal education and developed through years of experience. Clashes of opinion among experts are therefore thought to represent differences in traditions, conflicts between world views that are presumed to be coherent and stable. This assumption is pervasive. For example, it underlies the use of a "hit list" by Environmental Protection Agency administrators to exclude scientists from participating in review panels on the basis of their presumed judgment policies (Marshall, 1982). But is it true?

If experts were to make the same substantive judgment about the same set of objects under different task conditions, would they exhibit stable individual styles? Would the application of their expert opinion involve the same judgment policy despite variation in the details of the task?

The common view would predict that differences among individual experts would be stable enough to withstand the influence of variations in task condition. This assumption underlies the discussion of the importance of individual styles in the design of decision support systems reviewed by Sage (1981). Another view would argue that the influence of the task conditions upon the cognitive processes involved in the judgments may be large enough to override differences in individual judgment policies (Brunswik, 1956; Hammond, 1955). It has been shown, for example, that college students' judgments may be influenced by details of the task (e.g., response mode, Lichtenstein & Slovic, 1971), and that experts' performance of statistical inference on abstract word problems may deviate systematically from the norm due to use of heuristic shortcuts (Einhorn & Hogarth, 1981; Kahneman, Slovic,

& Tversky, 1982).

The study of highway experts' judgments of safety reported in Hammond, Hamm, Grassia, and Pearson (1983) provided an opportunity to test the stability of individual judgment policies in expert decision makers. In that study 21 highway engineers from government, private industry, and university settings judged the safety of 39 highways under three conditions. Each condition was designed to induce either intuitive, quasi-rational, or analytical cognition. The experts devoted much time to their judgments, and the task characteristics involved a variety of judgment conditions that are involved in an engineering environment. Since each expert judged the same set of highways in each condition it is possible to address the following questions: Did an expert use the same judgment policy in each task condition? More specifically, were an expert's judgments of the safety of the highways in one task condition more similar to his judgments in the other task conditions than they were to the judgments of the other experts in the same task condition? Two approaches were used to explore these questions: examination of correlations among performances and cluster analysis of performances.

<u>First approach: Correlations among Performances</u>

The average intercorrelations between the different individuals' performances on the same task condition and between the same individual's performances on the different task conditions are presented in Table 1. The mean intra-task correlation is .56 and the mean intra-individual correlation is .50. (These may be compared with the mean correlation of .50 between the expert's judgment and the true answers.) Although the mean intra-task similarity is higher than the mean intra-individual similarity, there is much overlap. Further, the wide variation in the correlation scores suggests that

for some individuals similarities due to task condition are greater than similarities due to stability of individual judgment policy, whereas for others the reverse is true. Thus, this analysis of correlations among performances gives equivocal evidence that task conditions have a slightly stronger role in determining similarities among experts' performances than stable individual differences have.

Insert Table 1 about here

Second approach: Cluster Analyses of Performances

Cluster analysis makes it possible to determine whether groups of similar performances are made up of performances by the same individuals over different task conditions, or of performances by different individuals under the same task conditions. If each cluster produced by the analysis consisted of the performances of a different subset of individuals over all three conditions, we would conclude that each cluster represented a group of experts with stable judgment policies, and that individual judgment policies are robust under variation of task conditions. On the other hand, if each cluster consisted of the performances in one particular condition by all individuals, we would conclude that specific task conditions dominate individual differences in determining judgment policy when experts judge highway safety.

Method

Performance

An expert's performance in judging safety under the intuitive or quasi-rational condition consisted of the judgments he made for each of 39 highways. In the analytical condition the expert composed a formula for determining highway safety, and performance consists of the answers produced by applying the formula to each highway. Since 7 of the 21 experts made errors in constructing their formulas which would have produced unintended answers and thus would have obscured the stability of their individual approaches to judging highway safety, these errors were corrected.

Description of Judgment Policy

Ten dimensions pertaining to safety, such as lane width and number of curves per mile, were measured for each highway independently of the experts' judgments. These dimensions were used to made a linear model of the expert's judgments (or of the answers generated from his formula) under each task condition. The beta weights from these models indicate the relative weight or importance the expert placed on each dimension under that condition.

Beta weights are commonly used to describe judgment policies. However, they contain information only about the linearly predictable portions of a set of judgments. To guard against possible loss of information about systematic nonlinear use of cues, both the experts' beta weights and the answers themselves were used as descriptions of the experts' judgment policies for cluster analysis. Thus, cluster analyses were performed in parallel on profiles representing the experts' judgments of the highway (39 dimensions) and profiles representing their beta weights from the linear model of those

judgments (10 dimensions). There were 62 profiles of judgments of highways, 3 for each of 21 experts performing in each condition (intuitive, quasi-rational, and analytical), with the exception of one expert whose intuitive answers were incomplete. There were 63 profiles of beta weights for the second cluster analysis, since the expert with incomplete data was included, enough of his answers being available to allow construction of a regression model.

The cluster analyses were carried out with the BMDP2M program (Dixon, Brown, Engelman, Frane, & Jennrich, 1977). The measure of similarity was the intercorrelation between profiles. From the tree display output of this program, clusters were identified according to the following criteria:

1. Each cluster had to have at least 10 members.

2. Two clusters with ten or more members each would not be combined, but rather would be considered distinct clusters.

3. Every item that did not fall into a cluster identified according to these criteria was swept into the class of "outliers".

Results

The composition of the clusters was examined with respect to the number of profiles in each that were produced under the same task conditions or by the same experts.

The Role of Task Condition in Determining Clusters

1. Clusters of highway judgment profiles.

Three clusters and 13 outliers were identified in the highway judgment profiles. Table 2 shows the number of profiles in each cluster, the number of each task condition that would be expected by chance if task condition were not related to cluster membership, and the number that actually appeared. A chi-squared test of each cluster shows that the distribution of profiles is significantly different from chance, and, therefore, task conditions had a determining role in producing the clusters. The task distribution for the set of outliers is not significantly different from chance.

Insert Table 2 About Here
----

2. Clusters of beta weight profiles.

Two clusters and 4 outliers were identified in the beta weight profiles. Table 3 shows the number of profiles in each cluster and the number of each task condition that would be expected and that was observed. Chi-squared analysis of these data also show that task had a determining role in producing the clusters. The set of outliers was tested by the procedure outlined in the appendix, and was not significant.

Insert Table 3 About Here

The Role of Stable Individual Differences in Determining Clusters

Although the above analysis showed that the task condition played a significant role in determining cluster membership, stable individual differences might also have played such a role. That possibility was tested for each cluster analysis by determining whether performances of individuals were concentrated significantly in single clusters.

1. Clusters of highway judgment profiles.

Table 4 shows that there were a number of experts for whom the profiles of judgments under two or three different task conditions were similar enough to appear in the same cluster: two in Cluster HJ-2 (experts 4 and 20) and three in Cluster HJ-3 (experts 5, 10, and 17--including all three of expert 5's performances). Additionally, three experts (3, 9, and 13) had two performances that were outliers.

Insert Table 4 About Here

As some such clustering of individuals would be expected to occur by chance, a procedure for determining the probability of the observed distribution pattern was applied (see Appendix). The even distribution across individuals in clusters HJ-1 and HJ-2 was marginally significant, a result that is the opposite from what would be expected if stable individual differences in experts' judgment policies determined the pattern of similarities among their judgments.

2. Clusters of beta weight profiles.

The data from the two clusters and the set of outliers are shown in Table 5. As there were three tasks per expert and only two clusters, there must be pairs from the same expert in one or the other cluster. However, the experts were distributed significantly more evenly among the clusters than would be expected by chance.

Insert Table 5 About Here

In summary, the cluster analysis method shows strong evidence that task conditions, rather than stable individual differences, determine similarities among judgment performances and judgment policies.

Discussion

The cluster analysis approach offers more insight into the relative importance of task conditions and stable individual judgment policy in determining experts' judgment performances than does the approach of comparing within-task and within-individual correlations. Comparing the distributions of correlations reveals that the intra-task correlations are slightly higher, on the average, than the intra-individual correlations, but the variability is so high that interpretation is difficult. Making further use of these correlations to produce clusters of similar performances allows us to ask whether membership in these clusters is determined by task, by individual, or by both. It was clearly task conditions, and not individual style, that determined cluster membership. Thus the cluster analysis approach offers an unambiguous answer to the question, while the correlation approach does not.

It is curious that the cluster analysis of the safety judgments of the 39 highways produces three distinct clusters, whereas the cluster analysis of the beta weights on the 10 dimensions in the linear models of the individual experts' judgments produces only two clusters. Inspection of Tables 2 and 3 shows the nature of those clusters. With the judgments, one cluster involves mainly judgments produced under the intuitive task conditions, another mainly quasi-rational judgments, and the third mainly analytic judgments. With the beta weights, one cluster involves mainly the linear models of judgments under the intuitive task conditions and the other mainly models of both quasi-rational and analytic judgments.

The judgments produced by the quasi-rational and analytical tasks are more distinct from each other than are the linear model descriptions of these same judgments; that is, distinct patterns of judgments are fit by linear models that are not distinct. How is this to be explained? There may be something in common among the nonlinear portions of the quasi-rational judgment policies that is distinct from the nonlinear portions of the analytic judgment policies (formulas). This could cause the quasi-rational and analytical performances to be grouped separately in the cluster analysis of the highway judgments (which contain both linear and nonlinear portions of the judgments as well as noise), but to be grouped together in the cluster analysis of the beta weight data, where the distinct nonlinear portions of the judgment strategies have been excluded.

Conclusion

In this study the task characteristics had a stronger role than stable individual judgment policies in determining similarity among experts' performances in a highway safety judgment task. The results support the view that the task conditions under which expert judgments are made play a very important role in determining how those judgments are made, and consequently in determining the judgments themselves.

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Table 1

Average Intercorrelations Within Task and Within Individual

Correlations among Different Individuals on Each Task Condition*:

	Lowest	Mean	Highest	N
Intuitive	.06	.58	.86	20
Quasi-rational	-.20	.47	.82	21
Analytic	-.18	.63	.93	21
Mean within task condition correlation for all three task conditions:		.56		

Correlations among different task conditions (I = intuitive, Q = quasi-rational, A = analytical) for the same individual:

	Lowest	Mean	Highest	N
r(I,Q)	-.01	.43	.67	20
r(I,A)	-.01	.49	.66	20
r(Q,A)	.06	.56	.87	21
Mean of the three r's for each individual:	.06	.50	.68	21

Correlations between individual judgments of highway safety and the true safety of the highways, for each task condition.

Intuitive	Quasi-rational	Analytical	Mean
.53	.48	.49	.50

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* The mean correlation for the analytical task condition here is different from that reported in Hammond, Hamm, Grassia, and Pearson (1983) because here we treat errors in the analytical formulas liberally, while there we treated them conservatively.

Table 2

Clusters of Highway Judgments

The expected and observed numbers of performances in each task condition that fell into each of the three clusters of highway judgments.

Cluster	N	Task	Expected	Observed	Chi-squared	Significance
HJ-1	12	I	4	11	18.5	$p < .001$
		Q	4	0		
		A	4	1		
HJ-2	18	I	6	1	13.0	$p < .01$
		Q	6	13		
		A	6	4		
HJ-3	19	I	6.33	3	14.0	$p < .001$
		Q	6.33	2		
		A	6.33	14		
Outliers	13	I	4.33	5	2.0	NS
		Q	4.33	6		
		A	4.33	2		

Table 3

Clusters of Beta Weights

The expected and observed numbers of performances in each task condition that fell into each of the two clusters of beta weights.

Cluster	N	Task	Expected	Observed	Chi-squared	Significance
BW-1	26	I	8.67	21	27.77	$p < .001$
		Q	8.67	0		
		A	8.67	5		
BW-2	33	I	11	0	18.73	$p < .001$
		Q	11	20		
		A	11	13		
Outliers	4	I	1.33	0		NS, $p < .32$*
		Q	1.33	1		
		A	1.33	3		

* Exact probability (see Appendix).

Table 4

Distribution of Individuals in Clusters, Highway Judgments

The expected and observed numbers of performances by each expert that fell into each of the three clusters of highway judgments.

	Cluster			
	HJ-1	HJ-2	HJ-3	Outliers
N	12	18	19	13
Expected	.60	.86	.91	.62
Observed: Expert #				
1*	0	1	0	1
2	0	1	1	1
3	0	0	1	2
4	1	2	0	0
5	0	0	3	0
6	1	0	1	1
7	1	1	1	0
8	1	1	1	0
9	0	1	0	2
10	0	0	2	1
11	1	1	1	0
12	1	1	1	0
13	0	0	1	2
15	1	1	1	0
17	0	1	2	0
19	1	1	0	1
20	1	2	0	0
21	1	1	1	0
22	1	1	1	0
23	0	1	1	1
24	1	1	0	1
Probability of observing a pattern:				
This concentrated or more:	1.0	.995	.716	.440
This concentrated or less:	.059	.046	.342	.799

*Expert 1 did not have an intuitive performance.

Table 5

Distribution of Individuals in Clusters, Beta Weights

The expected and observed numbers of performances by each expert that fell into each of the two clusters of Beta Weights.

	Cluster		
	BW-1	BW-2	Outliers
N	26	33	4
Expected	1.24	1.57	0.19
Observed: Expert #			
1	2	1	0
2	1	2	0
3	1	1	1
4	2	1	0
5	1	2	0
6	1	2	0
7	1	2	0
8	2	1	0
9	1	1	1
10	1	2	0
11	2	1	0
12	1	2	0
13	1	1	1
15	2	1	0
17	1	1	1
19	1	2	0
20	1	2	0
21	1	2	0
22	1	2	0
23	1	2	0
24	1	2	0

Probability of observing a cluster:

	BW-1	BW-2	Outliers
This concentrated or more:	1.0	1.0	1.0
This concentrated or less:	.001	.004	.814

Appendix

A method has been developed and computerized for determining the probability that a sample from a universe of C categories, E exemplars per category, should have any particular distribution of exemplars over categories. As it is possible to order the possible distributions according to the degree that the exemplars are concentrated in a few categories, the method also calculates the probability that an observed distribution could have been this concentrated or more (or less) by chance.

This method is useful, as in the present study, for determining whether a cluster of performances has a disproportionately high or low number of performances by the same individuals. More generally, it is useful for determining whether a distribution of objects over a group of individuals is significantly "unfair", i.e., more concentrated than would be expected by chance. In effect, the method provides a substitute for the Chi-Squared test with equal expected frequencies. It gives the exact probability of the observed distribution even when the expected frequency per category is less than 5. (If the expected frequency per category is much greater than 5, however, chi-squared is preferable to the present method because it is computationally quicker.)

In the present study there was a universe of 21 experts (categories), 3 performances (exemplars) each. Clusters of size N were produced. Were the experts' individual identities influential in determining cluster membership? The observed distribution of performances over experts in the cluster may be

represented as a row of numbers r_i ranging from r_0 to r_3.

Table A-1

Index, i	0	1	2	3
Cell value, r_i	r_0	r_1	r_2	r_3
Very concentrated example pattern for a 12-performance cluster	17	0	0	4
Very non-concentrated example pattern for a 12-performance cluster	9	12	0	0

The indices i represent the number of performances an expert could have in a given cluster. The cell values, r_i's, represent the number of experts who had i performances in the cluster. The sum of the r_i's equals 21, the total number of experts. The sum of (i times r_i)'s equals the total number of performances in the cluster.

To determine how often the observed pattern could occur as opposed to other possible patterns, it is necessary to consider the other possible patterns as well. The method involves these steps: (a) listing each possible pattern as a row in a table, (b) arranging the rows in decreasing order of concentratedness, (c) calculating the number of possible ways that each pattern could occur, (d) determining the position of the row that represents the observed distribution, and finally (e) summing over the rows up through the row representing the observed distribution, in order to determine the likelihood that a distribution this concentrated or more (or less) would occur. We demonstrate the method by considering a cluster of size 4.

Step 1. Producing the table.

There are 4 columns in the table, corresponding to an individual having $i = 0, 1, 2$, or 3 performances in the cluster. The column entry, r_i, indicates the number of individuals who had i performances in the cluster. Each row of the table represents a different pattern of distributions of 4 performances over individual experts. Thus the first row represents a cluster with high concentration of performances on a few individuals: one individual had three performances and another individual had the fourth. The second row represents a cluster made up of two performances from each of two experts. The fourth row has the lowest concentration pattern, one performance from each of 4 experts.

Table A-2

i = Number of performances by an individual.

	0	1	2	3
Row 1	19	1	0	1
Row 2	19	0	2	0
Row 3	18	2	1	0
Row 4	17	4	0	0

Step 2. Ordering the rows.

The rows must be arranged in order of concentratedness. An index of concentratedness is provided by adding how many performances were in the cluster from the j most-concentrated experts, as j goes from 1 to 21 (the number of experts) or to 4 (the number of performances in the cluster), whichever is smaller. Generally, the formula for calculating the index of

concentratedness for a row is:

$$\sum_{j=1}^{N} \quad (r_i \text{ for the j most-concentrated experts})$$

where N = the number of experts or number of performances, whichever is less.

Table A-3

Demonstration of the procedure for calculating, From Table A-1, the number of performances by the j most-concentrated experts, as j varies from 1 to 4.

	j				
	1	2	3	4	Sum
Row 1	3	4	4	4	15
Row 2	2	4	4	4	14
Row 3	2	3	4	4	13
Row 4	1	2	3	4	10

Comparing the indices of concentratedness for Rows 1 to 4, in the rightmost column of Table A-3, shows that the rows in Table A-2 are in the required order. Otherwise they would need to be rearranged in order of decreasing concentratedness.

Step 3. Calculating the number of ways that each row could happen.

Table A-2 simply enumerates the possible patterns of distribution of performances over experts for clusters of size 4, regardless of the individual identities of the experts with each number of performances. In order to calculate the probability of getting the pattern represented by a row, the number of ways the row's pattern could happen must be calculated.

This calculation requires addressing two questions:

1. In how many possible ways could the experts be distributed over the cells in a given row? Thus, for Row 1 of Table A-2, expert 1 might have had three performances and expert 2 one performance, or expert 1 three and expert 3 one, and so on.

2. In how many ways could each expert have had the number of performances he got? E.g., if an expert had two performances, and there are three possible performances (intuitive, quasi-rational, and analytical), then there are three possible pairs of performances that he could have had. There is only one way he could have had three performances.

Question 1. This question has to do with the identity of experts. Calculating all the possible ways of distributing C = 21 experts over the cells of a given row is done by multiplying together the answers to a sequence of questions, one question per column. The first question is: in how many ways could r_0 experts have had 0 performances? The answer is

$$\binom{21}{r_0} \qquad \text{i.e.,} \quad \frac{21!}{(r_0)! * (21 - r_0)!} \; ,$$

the number of possible combinations of 21 experts taken r_0 at a time. The second question considers the remaining experts. How many ways could r_1 experts out of $(21 - r_0)$ have 1 performance? The answer is:

$$\binom{21 - r_0}{r_1}.$$

This process is done repeatedly until there is

$$\binom{21 - r_0 - r_1 - r_2}{r_3} \text{ or } \binom{r_3}{r3} \quad \text{or } 1$$

way of assigning the remaining r_3 experts to the last column in the row. These binomial coefficient terms are multiplied together to produce a term expressing the number of possible ways that the C = 21 experts could be assigned to the sets of size i in the pattern expressed by the row's r_i values. Generally:

$$\binom{C}{r_0} * \prod_{j=1}^{C} \binom{C - \sum_{i=0}^{j-1} r_i}{r_j}$$

Question 2. This question has to do with the identity of performances within experts. That is, in how many ways could each expert have his given number of performances? Each expert's assigned number of performances are drawn from a universe of three: the intuitive, quasi-rational, and analytical performances. There are 3 ways he could have 1 of them, 3 ways he could have 2 of them, but only one way he could have none of them and only one way he could have all three of them. Generally, there are

$$\binom{E}{i}$$

possible ways the expert could have i performances in a cluster if the maximum

number of performances possible per expert is E. The product of these terms for each of the 21 experts is the number of possible ways for particular performances to be distributed to the experts, given the pattern of concentration expressed by the row.

$$\prod_{i=0}^{E} \binom{E}{i}^{r_i}$$

Multiplying together these two expressions, representing the number of ways that the C = 21 particular experts could be assigned to the given collection of set sizes and the number of ways that the E = 3 particular performances could be assigned to each expert, produces the total number of ways that the pattern of distributions represented by a row could be obtained.

Step 4. Determining the position of the observed pattern in Table A-2.

In the present study, the group of outliers that had only 4 members had the pattern corresponding to Row 4 of Table A-2.

Step 5. Calculating the probability of a given row.

The previous step calculated the number of possible ways that a row's pattern could occur. Dividing it by the total number of ways that all possible patterns could occur gives the probability of a row of exactly this pattern of distribution, or concentratedness. The total is given by the sum of the number of possible ways all patterns could be obtained. It is also given by

$$\binom{21 * 3}{4}$$

i.e., the binomial coefficient of the number of items in the universe (number of experts times number of performances per expert) over the number of items in the cluster. Thus the probability of getting exactly the pattern observed in the example is .81.

Summing the rows up to and including the observed row give the probability that a pattern this concentrated or more could occur, 1.0. Summing the probabilities for all rows from the observed row to the bottom of the table gives the probability that a pattern this concentrated or less would occur, .81.

Table A-4 shows the number of possible ways each row could occur and the probabilities of observing a pattern with a concentratedness equal, greater than or equal, or less than or equal to the given row.

Table A-4

	Num. of possible ways the pattern could occur	Probability of that row	Probability of the row or less	Probability of the row or more
Row 1	1260	.002	1.000	.002
Row 2	1890	.003	.997	.005
Row 3	107730	.181	.995	.186
Row 4	484785	.814	.814	1.000
Total	595665	1.000		

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